Comparison of radial basis function and sequential Gaussian simulation: A review on application in mineral resource estimation

by J.M. Maponya[1], I. P. Dikgwatlhe[2], T. Chauke[2]

Affiliation:
1 Department of Earth Sciences, Faculty of Science, Engineering and Agriculture, University of Venda, South Africa.
2 Department of Mining, Minerals and Geomatics Engineering, College of Science, Engineering and Technology, University of South Africa, South Africa

Correspondence to:
J.M. Maponya

Email:
mapulajulia4@gmail.com
Julia.Maponya@univen.ac.za

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ORCiD:
J.M. Maponya,
https://orcid.org/0000-0002-7912-684X
I. P. Dikgwatlhe
https://orcid.org/0000-0003-4093-2139
T. Chauke
https://orcid.org/0000-0002-8535-0784

Abstract

Accurate mineral resource estimation is crucial for optimising mining operations, reducing financial risks, and ensuring efficient resource utilisation. Various spatial modelling techniques have been developed to estimate ore grades and geological continuity, among which radial basis function interpolation and sequential Gaussian simulation are widely used. This review paper provides a comparative analysis of these two methods, examining their theoretical foundations, applications, strengths, and limitations in mineral resource estimation. Radial basis function is a deterministic interpolation method that models spatial relationships based on radial distance functions, making it effective for capturing smooth geological trends. Although kriging techniques have historically dominated the mining sector, new developments have brought to light their shortcomings, especially when handling sparse datasets and grade uncertainty. The paper examined case examples that demonstrate the usefulness of radial basis function and sequential Gaussian simulation in estimating mineral resources, with an emphasis on how they can model grade distributions, measure uncertainty, and maximise financial results. There is a substantial study gap dealing with the comparison of both methods; despite their respective advantages, a head-to-head comparison of radial basis function and sequential Gaussian simulation is still not well-studied. Their relative advantages, computational effectiveness, and compatibility with other geostatistical methods should all be assessed in future research. Guidelines for selecting estimating techniques based on geological conditions and project objectives are given to practitioners. The review emphasises how geostatistical techniques must be continuously improved to improve resource estimation precision and facilitate well-informed mining sector decision-making.

Keywords
Radial basis function, sequential Gaussian simulation, mineral resource estimation, geostatistics, spatial uncertainty, ore grade modelling

Introduction

Today's mining operations, particularly underground mining, rely heavily on geostatistical methods to estimate mineral resources (Oltingey, 2024). Mineral resource estimation methods are used to estimate the tonnage and grade of a mineral deposit using data from exploration drilling, sampling, and geological interpretation (Rossi, Deutsch, 2014). One of the crucial steps in mine planning and design is estimating ore grade (Balci, Kumral, 2024). In South Africa, several mining operations have experienced financial losses due to inaccurate ore grade estimation (Minnitt, 2017). Ore grade estimation typically relies on limited drillhole data. This is because of the time and financial constraints required to drill, collect, and analyse drillhole cores (Atalay, 2024). The limited drillhole data that are available must be used carefully to accurately estimate the spatial distribution of the target ore grade. This estimation is important for various purposes such as evaluating economic feasibility of the mining project. Furthermore, it assists in making investment decisions for the deposit, short and long term mine planning, and estimating the lifespan of the mine (Blomo et al., 2019, Rossi, Deutsch, 2014).

Modern mining operations, particularly underground mines, rely strongly on geostatistical methods for mineral resource estimation (Oltingey, 2024). Mineral resource estimation refers to the determination of the tonnage and grade of a mineral deposit using information obtained from exploration drilling, sampling, and geological interpretation (Rossi, Deutsch, 2014). Estimating ore grade is a critical step in mine planning and design because it directly influences economic evaluation and operational decisions (Balci, Kumral, 2024). In South Africa, several mining operations have experienced financial losses due to inaccurate ore grade estimation (Minnitt, 2017).

Comparison of radial basis function and sequential Gaussian simulation

Ore grade estimation typically relies on limited drillhole data because of the time and financial constraints associated with drilling, collecting, and analysing drillhole cores (Atalay, 2024). The available data must therefore be used carefully to estimate the spatial distribution of ore grades within the deposit. Reliable estimation supports the evaluation of the economic feasibility of a mining project, informs investment decisions, guides short and long term mine planning, and assists in estimating the expected life of mine (Blomo et al., 2019; Rossi, Deutsch, 2014).

There are several methods that are used to estimate ore grade for block modelling. These methods include geostatistical methods such as kriging and its variant, and implicit methods such as radial basis functions and signed distance functions (Oltingey, 2024). Additionally, machine learning methods are other methods that are used for estimating grade (Kumar et al., 2020). This paper focuses on radial basis function (RBF) interpolation and sequential Gaussian simulation (SGS) and their applications in mineral resource estimation.

Radial basis functions (RBF) are implicit methods that are used to estimate the spatial variability of a variable by fitting a continuous surface over the sample data (Majdisovaa, Skala, 2018). The value in the function depends on the distance from the centre to the input space (Chen and Bakshi, 2009). When standard kriging is not feasible due to the inability to compute an experimental variogram, radial basis functions might be utilised as a substitute technique for estimating mineral resources (Santos, Yamamoto, 2019). To effectively interpolate large drillhole data sets for orebody implicit modelling, it is advisable to optimise the RBF equation's solution using the two-level domain decomposition technique (Zhong, Wang, 2019).

On the other hand, there is sequential Gaussian simulation (SGS), which is a geostatistical method for simulating spatial correlated data values at unsampled locations (Fatemeh, 2013). It is a technique used to generate multiple realisations of a random field, such as a geological deposit, based on a limited set of measurements. Sequential Gaussian simulation achieve a Gaussian transformation of the data and realisations of regular random variables. SGS can be used to map the spatial distribution and uncertainty of metals for geochemical, and it is found to be more effective than traditional kriging methods for this purpose (Fengrui et al., 2012).

As highlighted from the few reviewed studies in the aforementione, RBF and SGS have been extensively used in mineral resource estimation. However, these methodologies are scattered across the literature, with no systematic collection that may be used as a complete reference or knowledge base (Oltingey, 2024). As a result, this paper compiles the scattered knowledge from the literature into a single comprehensive review that can be used as a reference for future research and practical applications.

The primary goal of this paper is to provide a comprehensive review of radial basis function (RBF) interpolation and sequential Gaussian simulation (SGS), with an emphasis on its applications in mineral resource estimates. This is performed by reviewing various research studies. Relevant literature was gathered from trustworthy academic resources such as Google Scholar, ScienceDirect, and Web of Science. A keyword-based search method was used to find relevant studies. This review covers peer-reviewed journal articles, theses, dissertations, and peer-reviewed conference papers published between 2012 and 2024.

The structure of this review paper follows the introduction, methodology, practical applications and comparison of SGS and RBF in resource estimation; this covers the case studies on each method in the real-world application for resource estimation. Each method is reviewed separately with discussions, which recap the main comparisons between SGS and RBF, emphasising their respective strengths and limitations in resource estimation. Recommendations for practitioners on when to choose SGS or RBF based on the context and objectives of resource estimation projects are provided. Lastly, concluding remarks on the importance of continued research and development in geostatistical methods for resource estimation.

Methods and materials

An extensive literature review was done to identify the most relevant peer-reviewed publications and research dissertations. The scientific research databases such as Google Scholar, Scopus, Science Direct and Web of Science were used to search for publications. One of the most important methods used in searching the publications was the use of keywords. That helped with limiting the search within the scope of interest. Keywords used to search for papers included the following: mineral resource estimation, ore grade estimation, reserve estimation, ore block modelling, sequential Gaussian simulation and radial basis function.

The literature search resulted in 87 publications of journal articles, and students' dissertation and conference proceedings on mineral resource estimation. To narrow this, RBF and SGS were now included in the search to help find most relevant papers. On student's dissertation, only master's and doctoral papers were considered to ensure more relevance. Papers can be written and published in any language, in this case, papers published in English were considered and reviewed. The selected publications were reviewed with particular emphasis on their objectives, methodologies, findings, and conclusions. The publications were limited to 2012 to 2024, because most recent papers were needed for this review. The final research publications, book or textbook chapters, technical reports, and theses that were left after the narrowing were about 30. The publications reviewed in this paper are summarised in Table 1. The majority of the sources come from theses and dissertations of students, making up 5 publications reviewed. This is followed by the journal articles and conference proceedings.

Methodological review

Radial basis function

Alternative forms of radial basis functions are defined as the distance from another point denoted C, known as a centre, and are functions of which the value depends only on the distance from the origin (Majdisovaa, Skala, 2018). For a radial basis function to function, it must define itself in relation to its origin or centre. This is accomplished by factoring in the function's absolute value. The definition of an absolute value is a value devoid of its corresponding sign (positive or negative) (Buhmann, 2003).

The initial multiquadric equations put forward by Hardy (1971) are generalised by radial functions. Yamamoto (2002) states that Equation 1 can be used to express the estimator using multiquadric equations, and Equation 2 provides the constraint condition (Santos, Yamamoto, 2019).

$$Z^*(x_0) = \sum_{i=1}^{n} W_i\, Z(x_i) \qquad [1]$$

$$\sum_{i=1}^{n} W_i = 1 \qquad [2]$$

Table 1
Summary of the publications obtained from scientific research databases such as Google Scholar, Scopus, Science Direct, and Web of Science.

Source	Number (Articles, report, thesis, books)	Authors
Scientific Mining Journal	1	Atalay, 2023
Mining, Metallurgy and Exploration Journal	1	Balci, Kumral, 2024
International Journal of Mining, Reclamation and Environment	1	Blom et al., 2019
Book chapter	2	Buhmann, 2003
Nwaila et al., 2024		
Conference proceedings	2	Chen et al., 2021
Tenorio, Bandopadhyay, S, 2015		
Institute of Geological Survey	2	Chen et al., 2021
Fengrui et al., 2012		
Reports	3	Chen et al., 2016
Griffin, 2023		
Zhang, 2011		
Springer International	2	Gomex-Hernandez, 2023
Hillier, 2023		
Thesis	5	Chieundura, 2017
Goncalves, 2021		
Gulule, 2016		
Kassymkan, 2024		
Mabala, 2021		
Universal Journal of Geoscience	1	Fatemeh, 2013
Journal of the Chemical, Metallurgical and Mining	1	Krige, 1951
Journal of Emerging Technologies and Innovative Research	1	Kumar et al., 2020
Applied Mathematical Modelling	1	Maidisovaa, Skala, 2028
Jornal of Southern African Institute of Mining and Metallurgy	1	Minnitt, 2017
National Institute of Technology	1	Moharaj, Wangmo, 2014
Arabian Journal of Geoscience	1	Mojezi et al., 2013
REM-International Engineering Journal	1	Santos, Yamamoto, 2019
International Journal of Geo-Engineering	1	Tehernejad et al., 2018

The uncertainty associated with multiquadric interpolation can be calculated by the interpolation variance expression in Equation 3.

$$S_0^2 = \sum_{i=1}^{n}\left(Z(x_i) - Z^*(x_0)\right)^2 \qquad [3]$$

The value in the function depends on the distance from the centre to the input space (Chen and Bakshi, 2009). Radial basis function offers simplicity and faster computation without compromising the ability to map input-output data, while also providing greater flexibility. With proper model parameter tuning, it can effectively capture both linear and non-linear relationships (Yu, 2012). It requires adequate input space coverage, and RBF network centres are selected based on the distribution of the input data rather than the specific prediction task (Soper, 2023).

Sequential Gaussian simulation

Sequential Gaussian simulation (SGS) is a geostatistical method for simulating spatially correlated data values at unsampled locations (Fatemeh et al., 2013). It is a technique used to generate multiple realisations of a random field, such as a geological deposit, based on a limited set of measurements. Sequential Gaussian simulation achieves a Gaussian transformation of the data and realise realisations of regular random variables.

Using values from the surrounding area, a simulated value at a known point is randomly drawn from the conditional cumulative distribution function, which is defined by the kriging mean and variance. The simulated value is dependent on the initial data and earlier simulated values at a new randomly visited point. Up until every point in the grid has been simulated for every realisation, the process is repeated (Deutsch, Journel, 1992). SGS can be used to map the spatial distribution and uncertainty of metals for geochemical anomalies, and it is found to be more effective than traditional kriging methods for this purpose (Fengrui et al., 2012).

SGS reduces estimation smoothing, reproduces histograms, and provides a better representation of local variability. Additionally, it offers more accurate estimates that respect spatial variability and enables the assessment of global uncertainty (Gómez-Hernández, 2023). Using individual simulations can lead to high estimation inaccuracy, and data management issues may arise when many realisations are used. Furthermore, insufficient conditioning data in a simulation can cause significant variation between the realisations (Madsen et al., 2021).

It uses the following Equations 4 to 6 to generate multiple equally probable realisations of a spatially distributed variable, maintaining the statistical properties of the original dataset (Manchuk, Deutsch, 2012).

Normal score transformation:

$$y(x_i) = \phi^{-1}(F_z(z(x_i)))\ldots\ldots\ldots\ldots \quad [4]$$

Kriging estimation:

$$\hat{y}(x_0) = \sum_{i=1}^{n} \lambda_i y(x_i)\ldots\ldots\ldots\ldots \quad [5]$$

Conditional simulation:

$$y*(x_0) \sim N(\hat{y}(x_0), \sigma_k^2(x_0))\ldots\ldots\ldots\ldots \quad [6]$$

Difference between radial basis function and sequential Gaussian simulation

Although both methods are used to predict the spatial distribution of ore grades, they differ fundamentally in their objectives and underlying approaches (Fig.1). SGS is a stochastic geostatistical simulation method that generates multiple equally probable realisations of grade distribution, allowing the modelling of local variability and quantification of uncertainty. In contrast, RBF is a deterministic interpolation technique that fits a smooth continuous surface through sampled data points, providing computational efficiency but limited capability in representing uncertainty and high-grade spatial continuity. Figure 2 highlights the conceptual differences between SGS and RBF in terms of variability representation, uncertainty assessment, and interpolation behaviour (Gulule, 2016).

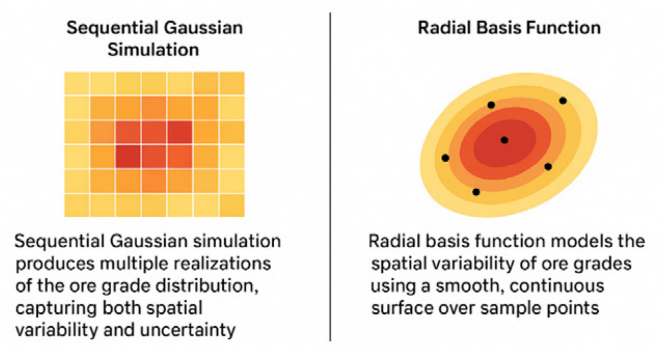

Figure 1—Difference between RBF and SGS (Gulule, 2016)

Comparative analysis of radial basis function and sequential Gaussian simulation

Case studies of radial basis function in resource estimation

Radial basis function (RBF) interpolation has developed as an important tool in implicit modelling, providing a flexible and economical method for spatial interpolation and resource estimation. Its capacity to create smooth, continuous grade models from unevenly distributed data makes it ideal for geologically complicated deposits. In mineral resource estimates, RBF is increasingly being used to simulate both geological boundaries and grade distributions, particularly in commercial software such as Leapfrog® Geo. The case studies that follow show how RBF-based methods have been used in a variety of geological settings, including their benefits, limits, and interaction with standard or hybrid modelling workflows.

The research work by Santos and Yamamoto (2019) analysed the use of radial basis functions, particularly the multiquadric equations, or gold resource estimation in the União Luiz and Morro do Carrapato deposits in the Alta Floresta Gold Province, Brazil. The study was motivated by the fact that the main direction of mineral continuity (90° strike) exhibited a pure nugget effect in the experimental variogram, indicating no spatial correlation. Ordinary kriging was not applicable as it usually requires specification of anisotropy ellipsoid through three or more well-defined directions of correlation. To overcome this difficulty, the researchers resorted to an approach known as radial basis function (RBF) interpolation, which does not rely on variogram modelling and yet shares some properties with kriging, such as a weighted average of neighbouring values. This interpolation approach assumed a three-dimensional block model obtained from 62 drill holes with over 9 million blocks each having dimensions of 408 × 120 × 190. Because the gold grades had highly positively skewed distributions, it was necessary to first transform the data onto Gaussian scale, perform interpolation based on multiquadric RBF, and then reverse the initial transformation.

The search was done using anisotropic ellipsoids with an octant-based neighbour selection and having a maximum of 16 surrounding points. Geokrige software was employed for the modelling process. From the findings, it was evident that the gold grades were distributed vertically showing evidence of structural control mineralisation, probably associated with quartz veins in

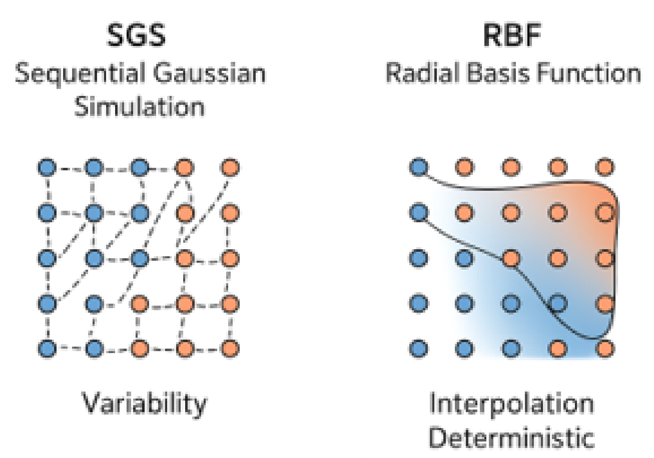

Figure 2—Conceptual illustration of the key differences between sequential Gaussian simulation (SGS) and radial basis function (RBF) interpolation (Gulule, 2016)

Table 2

The findings of the main parameters (Goncalves, 2021)

Parameter	Value/description
Coefficient of variation (CV)	6.85 - Indicates very high variability in gold content, typical for gold deposits.
Maximum gold assay	85.78 ppm - suggests the presence of native gold, reflecting extreme values in the data.
Upper quartile	25% of total samples exceed 0.18 ppm - Indicates a significant portion of low-grade samples.
Main direction variogram	Pure nugget effect - reflects a random distribution of gold mineralisation.
Orthogonal direction variogram	Structured variogram (180/85) - however, deemed ineffective for defining anisotropy ellipsoid for kriging.
3D model findings	Vertical distribution of gold - suggests structural control over mineralisation.
Estimated gold resource	2.122 tonnes - based on a grade-tonnage curve with a simulated cut-off of 5.0 g/tonne.

granodiorite host rocks. A high coefficient of variation (CV = 6. 85) indicated significant grade variability, including extremely high values potentially linked to native gold. According to the grade-tonnage analysis results, about 2,122 tonnes of gold could be considered as reserves at a 5.0 g/t cut-off grade. The total geological in situ resources were estimated to be 6.4 tonnes. Also, a variance model suggested that increased grade level was proportionally linked with greater uncertainty, thus supporting the common feature of lognormal distribution.

In their view, although effective in such cases where variogram-based geostatistics fail, application of RBF method has certain weaknesses. These weaknesses include the inability to consider spatial correlation at some important directions, low borehole density, skewed data and a need for choosing parameters carefully because, otherwise, it may lead to bias in estimation. The research backs RBFs as an acceptable substitute for the standard geostatistical assumptions that may fail. Nonetheless, it emphasises the need for one to first comprehend some attributes, such as deposit geometry and data behaviour of deposits, before employing these techniques. The study used the radial basis function to create 3D model and grade-tonnage curves (Fig.3), which were used for analysis and estimation of the mineral resource.

Goncalves (2021) studied resource estimation using radial basis function on a sparse dataset. The main objective of the study was to measure and contrast the effectiveness of RBF estimates in scenarios with low data coverage. This required comparing RBF's performance against alternative approaches like ordinary kriging in low data coverage. The modelled stratigraphic unit and geology

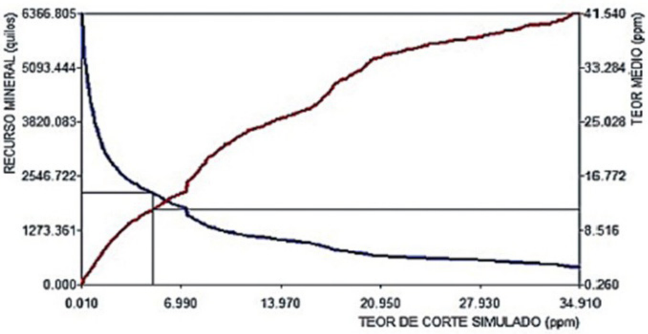

Figure 3—Gold grade-tonnage curve (Santos, Yamamoto, 2019)

aided in visualisation of the geological data.

Exploratory data analysis was used to generate sample composites, domain various populations, and analyse the data (Goncalves, 2021). Normal score transformation, semi-variogram modelling, and geostatistical analysis were performed on the datasets. To guarantee that the estimations were accurate, the best RBF parameters, such as spatial function and degree of polynomial in the drift model, were used. Three distinct estimation methods RBF, ordinary kriging (OK), and inverse distance weighting (IDW) were used to estimate grades into a block model.

The comparison of these methods enables a thorough assessment of the RBF method (Goncalves, 2021). To ensure the dependability of the results, statistical techniques were used to validate the model outputs against the inputs. According to the study, when there is enough data available, RBF and ordinary kriging (OK) produce results that are comparable. This resemblance implies that both approaches work well for updating grade control models in production settings with more data. The results provide credibility to the notion that RBF can be a good substitute for more conventional techniques like inverse distance weighting (Goncalves, 2021).

The results (Table 2) also show that kriging has a drawback, especially when dealing with sparse data. Estimates from kriging can be biased because of the small sample size, which could introduce edge effects. RBF, on the other hand, is not affected by this drawback because it functions as a global estimator, guaranteeing that estimates along domain boundaries are consistently assigned.

Griffin, 2023 examined the current drilling status of the Los Pumas Manganese project in Northern Chile, with an analysis conducted using the radial basis function method. The methodology involved modelling the manganese assay data using Leapfrog Geo and Surpac software. Ordinary kriging was employed on Surpac software using a 2.5% manganese cut-off grade. Wireframes were created using Leapfrog RBF modelling on 2% manganese composites (Griffin, 2023). The drillholes were composite for 1 m intervals to allow the performance of geostatistical analysis and grade estimation. The findings revealed the estimates of 30.3 million tonnes at 6.2% manganese. The mineralisation was predominantly horizontal and extends from surface to a depth of 60 metres (Griffin, 2023). The geological data in the dataset were not fully analysed, which could enhance the understanding of the deposit.

Comparison of radial basis function and sequential Gaussian simulation

Even though using one method is advised, comparison of different geostatistical methods is recommended for better results. Atalay (2023) compared the conditional radial basis function with ordinary kriging to estimate the calorific values of coal in the Türkiye-Thrace region. The main goal was to understand the two methods and assist towards informed decision-making regarding resource management. The investigation involved the use of previous research studies that employed these methods. A total of 128 drillhole data were collected, with a 38.326-metre drilling length. Individual coal seams were about 6.5 metres on average in thickness, and the total thickness of coal taken from these drillings was 876 metres.

After loading the data on Python, the data were composited into 1-metre intervals for both techniques. This was done to ensure that the data are uniform and relevant for analysis. Following this, an experimental variogram was estimated to assist in the kriging equations and RBF. The conditional radial basis function was employed to estimate the caloric values against the ordinary kriging. In contrast to kriging estimates, the results showed that RBF estimates were more in line with the composite estimates. Even though RBF yielded favourable findings, the minimum value that was obtained was 1 kCal/kg less than the composite minimum values. Although slight, this disparity raises the possibility of an RBF technique flaw because estimators are typically supposed to interpolate within the range of observed data. The summary of the results is shown in Figure 4.

Discussion

Radial basis function (RBF) interpolation presents several strengths in resource estimation, particularly in complex geological settings. One of its primary advantages is its flexibility in variogram modelling, as it does not rely on the formulation of an anisotropy ellipsoid or defined variograms. This capability is especially valuable in instances where traditional methods like ordinary kriging are ineffective due to pure nugget effects, as noted in the research by Santos and Yamamoto (2019). Additionally, RBF is adept at handling skewed data distributions, allowing for transformations to a Gaussian scale before interpolation, which enhances the accuracy of grade estimations. Its global estimation characteristic ensures consistency across domain boundaries, making it less susceptible to edge effects that can affect local estimators like kriging, particularly in sparse data scenarios, as demonstrated by Goncalves (2021).

However, the application of RBF also carries notable weaknesses. The efficiency of the method depends on the careful selection of parameters such as spatial functions and polynomial degrees in the drift model. Poor choices can result in biased estimates and inadequate representations of geological features. Furthermore, RBF does not account for spatial correlation in critical directions, potentially limiting its effectiveness in capturing the stratigraphic complexities of certain deposits. The performance of RBF can also be influenced by data density, with low-density datasets leading to misrepresentations and a reliance on additional data to validate estimations.

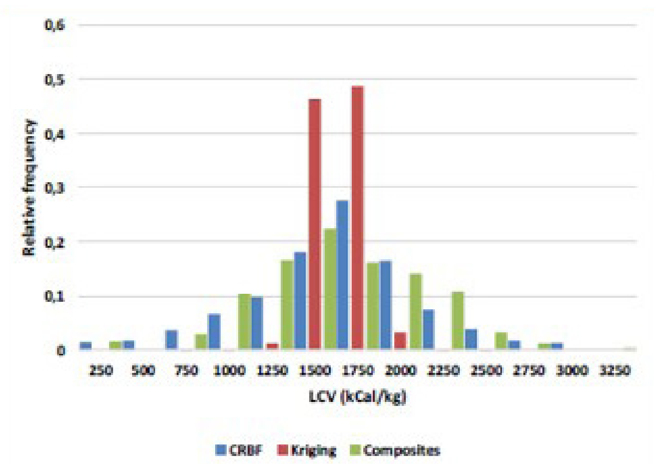

Figure 4—Histograms of RBF, kriging, and composites (Atalay, 2023)

The literature on RBF reveals significant gaps that require future research, particularly in the context of cross-method comparisons, as most studies evaluate RBF in focus on specific geological cases. There is an opportunity to systematically assess RBF's performance across diverse geological contexts and resource types while exploring its computational efficiency in large-scale modelling and conducting sensitivity analyses on parameter variations. Additionally, integrating geological insights into the RBF modelling process through data analysis could lead to improved resource estimations and a deeper understanding of the geological deposits.

Case studies of sequential Gaussian simulation in resource estimation

When planning open pits, grade estimation is crucial because, while over-estimation would unnecessarily raise the stripping ratio, under-estimation might lead to the loss of economic ore during the grade estimation procedure. Typically, grade estimate is done using the kriging method, which has the drawbacks of under-estimating and/or over-estimating because of the smoothing effect.

Conditional simulation is the more effective strategy that can be used to overcome the limitations of the kriging method, and it is applied to many disciplines for estimation and simulation of the process in place. This paper focused mainly on the application of mineral resource estimation.

Monjezi et al. (2013) applied sequential Gaussian simulation to model the spatial distribution of copper grade in the Sungun copper deposit, located in the northwest of Iran. Their study aimed to generate realistic grade realisations that honour the statistical characteristics of the sample data while capturing spatial uncertainty inherent in the deposit. By employing SGS, they were able to produce multiple, equally probable grade models, providing a robust basis for resource estimation and risk assessment in mine planning. This was done to compare sequential Gaussian simulation and ordinary kriging method for grade modelling. One important objective was to improve grade estimation and economic indicators in open-pit mining.

The results showed that conditional simulation is a good way to address the shortcomings of the kriging method. Additionally, it was noted that the grade distribution produced by the conditional simulation is nearly equal to that of the actual exploration data when compared to the kriging method. As a result, conditional simulation greatly increased the total of mineable ore and enhanced the average net present value, which is the mine's most important economic indicator, by 40%.

The study has several limitations in that it uses moderate-resolution data, which may reduce spatial accuracy, and does not account for temporal variations. The weighted overlay method assumes linear relationships, oversimplifying complex geostatistical interactions. Field validation was limited, affecting result reliability. Lastly, the findings are specific to the Sungun deposit and may not be generalised to other regions.

Comparison of radial basis function and sequential Gaussian simulation

Tenorio and Bandopadhyay (2015) studied platinum deposits close to Alaska's Goodnews Bay, applying sophisticated statistical techniques to the difficulties presented by marine placer deposits. The challenges included highly variable and discontinuous mineralisation, sparse and irregular sampling, and a complex deposition process. This entails examining the historical data and geological features gathered from the region since the 1980s, including 470 samples across a huge area of roughly 4000 square kilometres. Using sequential Gaussian simulation was one of the main goals for the analysis. This approach was selected because it can accurately estimate the platinum grades in the sampled locations by representing variables that have a normal distribution. Additionally, the study compared the outcomes of SGS with those of conventional estimating methods, particularly the inverse distance squared (ID^2) approach.

The purpose of this comparison was to assess SGS's efficacy and efficiency in generating accurate grade-tonnage estimations for different cut-off grades. To increase the dependability of the estimated resources, the study strengthened the confidence in geological reporting of the platinum deposit by making sure that the sampling's quality, density, and distribution are sufficient.

Sequential Gaussian simulation was used on ISATIS software to assess the platinum deposit. Before employing SGS, the sample grades were normalised using a normal score transform and handled as continuous variables. This stage is essential for ensuring that the data satisfy the SGS method's presumptions. Both methods demonstrated their efficacy in estimating platinum resources by producing comparable distribution maps and grade distributions for various cut-off grades. Sequential Gaussian simulation was found to be more 'grade/tonnage-efficient' for the cut-off range of 400 mg/m^3 to 200 mg/m^3. This suggests that this method provides a better balance between the estimated grade and the tonnage of platinum available (Tenorio, Bandopadhyay, 2015).

When compared to the inverse distance squared approach, the conditional simulation method yielded a smoother area versus cut-off curve, demonstrating the benefits of conditional simulation for a resource estimate. The study revealed that the small number of samples limited the ability to predict grades. Areas without samples or with 0 values could not be reliably approximated, even though appropriate grades were projected close to known samples.

The study revealed that SGS does not perform well on sparse sampling, which made it challenging to determine grades with accuracy in areas that were either poorly sampled or unsampled. The region's extremely irregular and varied mineralisation made precise SGS modelling difficult. Furthermore, it showed that if the data deviate greatly from normality, SGS may create mistakes because it requires normal score translation and presupposes a normal distribution of the data. Additionally, the study discovered that it was not possible to forecast grades in locations with zero values or without samples. Although SGS occasionally performed better than the inverse distance squared method, each approach had advantages and disadvantages that demonstrated how difficult it is to estimate resources in maritime placer deposits.

Chen et al. (2016), investigated how the copper ore body differs in Tibet regions with others in China. This was important because it helped with the effective resource management and extraction strategies of the ore body. One of the important goals was the delineation of the copper ore body to establish the ore body's limits and extent, which is essential for planning mining operations and making sure that resources are used effectively (Chen et al.,2016).

A comprehensive dataset comprising 33 exploratory trenches and 106 drill holes were used for the analysis. Descriptive statistics were used to summarise the copper grade data at the start of the investigation. A normal score transformation is applied to the copper grade data; this transformation is necessary for the efficient application of geostatistical approaches (Chen et al., 2016). To evaluate the spatial continuity of the copper grades, the study computes experimental semi-variograms. These semi-variograms give information about the ore bodies' spatial orientation by displaying their inclination angles and directional trends.

The study used sequential Gaussian simulation on tools such as SGeMS (Stanford Geostatistical Modelling software) and Datamine Studio for visualisations and statistical analyses (Chen et al., 2016). Ten realisations were produced on a 30 m × 30 m x 6 m grid, offering a thorough understanding of the distribution of copper. According to the analysis of the copper grades, the distribution exhibits a lognormal pattern. The semi-variograms revealed that the north ore body trends east-west with a 20-degree inclination, the east copper body is seen to flow north-south with a 75-degree inclination. Furthermore, with an inclination angle of 20 degrees and a tendency angle of 40 degrees, the west ore body advances towards 310 degrees. Planning extraction tactics requires an understanding of these directional tendencies (Chen et al., 2016). The table of results is shown table 3.

The study revealed that, if the data greatly deviates from the normal distribution assumption, bias may be introduced into the normal score transformation process. Even though the experimental semi-variograms offered valuable insights into spatial continuity, it is possible that they misinterpreted directional trends since they do not adequately take into consideration the intricacy of ore body structures. Furthermore, the study recognised that the reliability of the resulting grade estimations may be impacted by inaccuracies in the data, as the use of sequential Gaussian simulation severely depends on the quality and accuracy of the input data.

Gulule (2016) compared ordinary kriging with sequential Gaussian simulations on blast hole data having both high and low grade at the Kayelekera mine. This was coupled by comparing the grade distribution maps and grade tonnage curves from both methods. The data assisted in determining which technique gives accurate and better spatial variability of the data. Sampling from different geological units with different grades was done. The data were plotted, and statistical analysis was done using Hellman and Schofield's MP software. Estimation using sequential Gaussian simulation on micromine was done and compared with estimates on ordinary kriging. Both techniques produced similar results and same estimates, but for the areas with less grade, the profit dropped after reaching the maximum cut-off grade.

Sparse sampling from several geological units may affect the accuracy of grade estimations, especially in locations with low grades. Furthermore, sequential Gaussian simulation and regular kriging both gave findings that were comparable, but they had trouble accounting for profit declines in regions that were below the highest cut-off grade.

Chiwundura (2017) used multiple indicator kriging (MIK), a geostatistical method that helps in understanding the distribution of grades within the deposit and Sequential Gaussian Simulation to estimate the recoverable of the Nickel deposits. This was done together with the assessment of grade uncertainty and comparing it with historical estimates. The comparison was important because it helped with the validation of the new methods and track any changes in estimates over time. Multiple indicator kriging (MIK) was applied to determine the number of resources that could be recovered. Compared to more conventional approaches like ordinary kriging (OK), MIK is a non-linear geostatistical methodology that enables the insertion of several grade thresholds, offering a more detailed understanding of the grade distribution.

Sequential Gaussian simulation was used in conjunction with MIK to create a probabilistic uncertainty model. By creating numerous realisations of the grade distribution, this method samples from the uncertainty distribution and aids in evaluating the uncertainty surrounding the estimations. To comprehend the geographic continuity of the nickel grades, a thorough variography analysis was conducted as part of the study. The selection of the MIK methods over the median indicator approach was influenced by the two primary directions of grade continuity that this study revealed (Chiwundura, 2017).

Data from 172 drill holes served as the basis for both methods, which assessed the eastern and western domains of the Hunters Road western orebody. This large dataset was essential to the proper use of SGS and MIK. Out of the 172 validated boreholes, 15 boreholes did not have assay results because they did not intersect nickel mineralisation. This indicates a significant focus on the quality of data used for resource estimation. At an average grade of 0.57% Ni, the combined mineral resources estimate for the western orebody at a cut-off grade of 0.40% Ni was 32.30 million tonnes (Mt) of contained nickel metal. Both the MIK and SGS approaches were used to produce this estimate.

The SGS results showed that there was little uncertainty in the nickel grades, with a 90% chance that the average true grade would be higher than the cut-off and fall within +/-3% of the predicted block grade. For the western domain, the mean grades calculated by SGS were 0.55% Ni, while for the eastern domain, they were 0.57% Ni. The summarised results are presented in Table 3.

The lack of assay results from 15 boreholes, have impacted the resource estimate's accuracy, especially in regions devoid of nickel mineralisation. Although sequential Gaussian simulation and multiple indicator kriging offered comprehensive estimates, the study's dependence on historical data may have introduced inconsistencies if previously used methodologies diverged substantially from the present analysis. Furthermore, even though SGS showed low uncertainty in nickel grades, sampling density and data quality may still have an impact on how well both approaches estimate resource variability.

Table 3
Summary of key results from Nickel deposit (Chiwundura, 2017)

Metric	Value
Total drill holes	172
Total mineral resources Eetimate	32.30 Mt
Average grade	0.57% Ni
Contained nickel metal	183 kt
SGS mean grade (western domain)	0.55% Ni
SGS mean grade (eastern domain)	0.57% Ni
Probability of true grade	90% within +/-3%

Tahernejad et al. (2018) investigated the iron ore deposit at the Rezvan mine in Iran. Their study focused on incorporating ore grade uncertainty into mine planning to improve decision-making and optimise resource extraction. Understanding how grade uncertainty affects strategic mine planning decisions, specifically the net present value (NPV) of mining projects, and comparing the efficacy of sequential Gaussian simulation (SGS) and ordinary kriging (OK) in resource estimate were the main goals. The study used 3,483 powder samples taken from drilling operations in addition to data from 125 vertical exploration boreholes, guaranteeing a reasonably solid dataset for geostatistical modelling.

After analysing the data using descriptive statistics and geostatistical techniques, grade distribution models were created using SGS and OK. The results showed that, in contrast to OK, which tends to smooth grades and understate variability, SGS offered a more accurate depiction of grade variability, better reflecting spatial uncertainty. Because there was less chance of overestimating ore grades, SGS-based mine plans resulted in an enhanced net present value (NPV), proving that integrating grade uncertainty into planning can have a favourable impact on economic outcomes.

Even though SGS enhances uncertainty representation, it was noted that it is computationally more demanding than OK and necessitates more technical know-how and processing time. Another drawback was that the quality and density of the input data had a significant impact on the accuracy of the simulation results; no matter the technique, areas with sparse data or no sampling still carried a high degree of uncertainty. The study also recognised that the interpretation of NPV improvements between the two approaches may be considerably impacted by variations in the economic assumptions such as metal prices, discount rates, and operating expenses. Despite SGS's excellent performance, the authors pointed out that training and adaptation may be necessary for its application in operational mine planning, especially in mines accustomed to traditional estimation techniques.

Sotoudeh et al. (2020) focused on copper deposit and used sequential Gaussian simulation (SGS) to develop a comprehensive geological model for mine planning objectives. The first step was to use experimental algorithms to determine the underground stope layout. The second step involved creating a 3D block model of the study area, which was done by generating 50 realisations of the copper grade distribution using SGS. The last part was the validation of the simulated realisation by producing the histogram and variograms to confirm if they match the original data features.

The researchers found that the ore reserves of the kriging method were calculated to be 644 535 tonnes and geostatistical simulation produced 799 000 tonnes. According to the findings, a considerable percentage of underground mining limitations using the sequential Gaussian conditional simulation approach yield a higher economic value than ordinary kriging. Thus, the results demonstrate that standard kriging-based underground mine planning can provide misleading outputs, which can lead to erroneous expectations of net present value as well as mine production scheduling.

This is because traditional kriging methods are based on a single ore model that is supposed to be an actual deposit in the underground deposit being mined. They are unable to assess the uncertainty of the economic and operational repercussions of the stope layout. On the other hand, simulation methods provide an excellent opportunity to describe the distribution of ore grade in each realisation as well as quantify uncertainty.

Geochemical anomalies can also be assessed using sequential Gaussian simulations (Chen et al., 2021). The feasibility of the sequential Gaussian simulations was tested in mapping the geochemical anomalies as an alternative to ordinary kriging. Geostatistical interpolation method, also known as kriging, was applied to estimate the spatial distribution of lead (Pb) concentrations as compared to SGS to generate multiple realisations of lead spatial distribution (Chen et al., 2021). The first step that was taken was transforming the lead data into normal score before applying the SGS method. SGS was able to model the spatial uncertainty of lead geochemistry, but the ordinary kriging underestimated the true variability (Chen et al., 2021). From the findings, it can be concluded that SGS is a recommended powerful tool for spatial distribution and can be incorporated in mineral exploration and planning stage.

Mabala (2021) aimed to model gold deposit by simulating grade distributions within the A1 reef horizon using the TI and the direct sampling multiple point statistics technique (DeeSse), especially in regions with low sampling density. Integrating the uncertainty grade models into grade and tonnage curve computations, together with revenue and metal content estimates, was another important goal of the study. Comparing the outcomes from DeeSse and SGSIM is a crucial goal to assess their efficacy and identify any differences in the estimations generated by these techniques. The Tarkwa mine was the subject of the study. Given that the diamond drill holes in the pit expansion area are arranged roughly 200 metres apart along strike, 100 metres apart across strike, and 3 metres vertically, the dataset in this region is very sparse.

Sequential Gaussian simulation (SGSIM) was performed, and training images (TI) were created using Datamine StudioRM. Ar2Gems was used to run the DeeSse simulations since it was chosen for its capacity to implement the DeeSse method and was free to use for research. The e-type estimate of 50 SGSIM simulations was compared to the TIs to validate them. To show that DeeSse could replicate a greater range of grade values while still being comparable to SGSIM, the findings were additionally verified against SGSIM estimates (Fig.5).

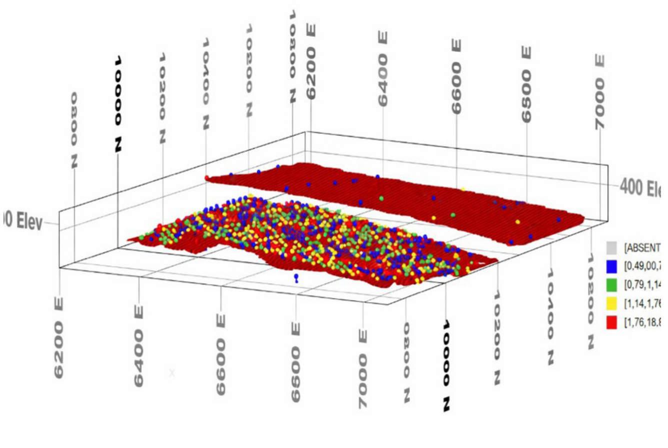

Figure 5—Block models within the TI area and EA (Mabala, 2021)

DeeSse was found to generate a wider range of grade values, suggesting that it can capture greater data variability. But SGSIM showed higher local variability, which could be useful in some situations. In comparison to ordinary kriging, the study found that DeeSse offered a more reliable approach with higher confidence in the estimates. This was particularly important for resource modelling in places with low data densities. The accuracy of both DeeSse and SGSIM simulations was constrained by the poor sampling density, particularly in the pit extension area. The quality and representativeness of the training images utilised in DeeSse had a significant impact on the outcomes' dependability. Furthermore, DeeSse's performance in zones with less information was unclear even though it was able to capture a greater range of grade variability.

Kassymkan (2024) investigated and contrasted the effectiveness of two geostatistical techniques, simple kriging (SK) and sequential Gaussian simulation (SGS). The study compared both approaches to determine which one could yield more accurate estimates for iron ore grades in mining operations. Another important aspect was to precisely categorise materials as waste or ore. Because it has a direct impact on resource management and economic viability, this classification was essential for making well-informed decisions in mining operations. The investigation started with an initial dataset of 2 230 grade values of iron ore that were gathered from a particular location. A comprehensive exploratory data analysis (EDA) was carried out prior to the application of any estimating approaches. Variogram analysis followed, which aided in choosing the correct parameters for the estimate techniques by revealing how the grade values change with distance.

The software ISATIS.neo, which is specifically made for geostatistical modelling, was used for all studies and simulations. By making it easier to apply kriging and simulation approaches, this program guarantees precise and effective calculations (Kassymkan, 2024). The findings showed that, in comparison to SK, SGS offers estimations that are more accurate and trustworthy. The Q-Q charts make this clear by demonstrating that the points from SGS match the original dataset more closely than those from SK.

According to the results, SGS typically predicted more tonnage at higher cut-off values, whereas SK may produce higher tonnage at lower cut-off values. The findings reveal that, while SGS exhibits a minor advantage, both approaches offer estimates of economic gain and metal quantity that are comparable. The specific characteristics of the mineral deposit and the goals of the study should guide the decision between SGS and SK. Understanding the advantages and disadvantages of each approach can improve the results of resource estimation.

Discussion

SGS continuously offers a more accurate prediction of grade distributions and spatial uncertainty than conventional techniques such as ordinary kriging across a variety of deposits, from copper and platinum to iron and nickel. Especially in well-sampled areas, it improves economic measures like NPV and resource classification accuracy. However, it needs reliable input data, processing power, and specialised knowledge, and its efficacy decreases in areas with sparse data. Even though SGS has drawbacks, incorporating it into mine planning is a major step forward for geostatistical modelling, particularly when paired with other methods like MIK or DeeSse for increased forecast accuracy.

SGS's usefulness in mine planning under uncertainty is limited by the rarity with which current research integrates its results with economic decision-making measures like cut-off grade optimisation or net present value. The issues presented by non-Gaussian, skewed, or zero-inflated datasets are not sufficiently addressed by most methods, which mostly rely on normal score transformation. Furthermore, variogram modelling is still very simple, with little investigation into the effects of model uncertainty on simulation outcomes. Additionally, SGS is not widely used across ambiguous geological borders or domains, and sophisticated validation methods beyond histogram comparison are lacking.

Conclusion

Mineral resource estimation is a problematic task, which involves a lot of uncertainties regarding the non-uniform geological formations and obtained results from the estimates. At the end of each estimation, whether a mineral resource is categorised as an ore or waste, the mining depends on that estimation. That is why it is important to choose the most accurate estimation method because the choice could affect the production and lead to loss of money. As mentioned in the introduction, the most used methods for estimating mineral resources are geostatistical techniques, which have been used to start most of the successful mining companies worldwide.

The finding from the reviewed studies shows that both techniques are powerful for resource estimations on most of the explored minerals. They revealed that the techniques can model mineral resource and calculate mineral reserves. Most papers were published before 2020 because there was limited research on these two methods since then. Not a lot of work has been done on RBF regarding mineral resource estimation as compared to SGS. Even though there is not a lot of work done on RBF, it was shown that it can perform more effectively than ordinary kriging. Most of the studies were comparing the RBF and SGS with ordinary kriging and conclusions were drawn that RBF and SGS perform better.

There is no paper that compared the performance of RBF and SGS in resource estimation, but each one was done individually. The inability of SGS to integrate with economic decision-making tools like net present value and cut-off grade optimisation limits its applicability in mine planning when uncertainty is present. Most of the research only use normal score transformation, which omits important issues with skewed, non-Gaussian, or zero-inflated data. Little consideration is paid to model uncertainty and how it affects simulation outcomes in variogram modelling, which is still very rudimentary. Furthermore, validation techniques hardly ever extend beyond histogram comparisons, and SGS is rarely used across intricate geological limits.

Notably, there is no investigation of spatiotemporal SGS, co-simulation of associated variables, or hybrid models that include AI or machine learning, and no back-analysis using actual production or grade control data. RBF's performance has not been thoroughly examined in a variety of geological settings, and it does not include sensitivity analysis on important factors like spatial functions and polynomial drift. Furthermore, including geological information into the modelling process is frequently overlooked in RBF research.

To increase the robustness and usefulness of both SGS and RBF in mineral resource estimation, future research should concentrate on refining validation methodologies, integrating operational and economic indicators, investigating hybrid models, and carrying out extensive cross-method and sensitivity studies.

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